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A review on applications of ANN and SVM for building electrical energy consumption forecasting

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ABSTRACT

The rapid development of human population, buildings and technology application currently has caused electric consumption to grow rapidly. Therefore, efficient energy management and forecasting energy consumption for buildings are important in decision-making for effective energy saving and development in particular places. This paper reviews the building electrical energy forecasting method using artificial intelligence (AI) methods such as support vector machine (SVM) and artificial neural networks (ANN). Both methods are widely used in the field of forecasting and their aim on finding the most accurate approach is ever continuing. Besides the already existing single method of forecasting, the hybridization of the two forecasting methods has the potential to be applied for more accurate results. Further research works are currently ongoing, regarding the potential of hybrid method of Group Method of Data Handling (GMDH) and Least Square Support Vector Machine (LSSVM), or known as GLSSVM, to forecast building electrical energy consumption.

Contents

1. Introduction

The development rate of countries around the globe currently are growing tremendously and is inevitable. The world population growth rate in 2012 is estimated to be about 1.096% [1]. The pattern of population rate around the globe is continuously growing annually, as shown in Fig. 1. The growing pattern of human population indicates that the demand for accommodation, nation development and others will also keep increasing. Complementary to all these developments, superfluous energy is needed to drive the global demand; and at the same time, the environment needs to be kept safe. Furthermore, the rapid expansion of residential and commercial areas also contributes to the increase of building energy consumption, especially by the industrial growth. At the same time, environmental issues must be taken into account in the development bustle, in order to reduce pollution, carbon footprint and greenhouse effect [2].

In Europe, 40% of the total energy use and 36% of total carbon dioxide emissions come from buildings [4]. Energy uses in office building in China had been reported by Yang et al. [5] in 2008, which consumed about 70–300 kWh/m^2 per year. This is 10 to 20 times higher than residential consumption. Besides that, the electricity consumption in Taiwan has increased to 229.20 billion kWh in 2009

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from 82.65 billion kWh in 1990 [6]. These show that the forecast of energy consumption has become a crucial need in estimating energy usage; hence, the best plan for the development and environment is utterly required. The energy consumption forecasting nowadays has become an important issue due to the consideration of many aspects such as the depletion of fuel, environmental impact and carbon dioxide emission. Energy consumption forecasting also plays a significant role in plans to improve energy performance, save energy and reduce the hazardous environmental impact. Moreover, forecasting also plays a vital role in decision-making and future planning which rely on accurate forecasting result.

In present, forecasting building energy consumption is difficult due to the complexity of the system inside the building. This is due to the varieties of loads and types of building built to satisfy the increase of population and occupations demand. The energy consumption forecasting in a particular building is usually influenced by many factors, such as electrical appliances or devices inside the building, geographical location of the building, and as well as the time range of building operation. The energy consumption of buildings is huge, around 40–45% of total energy consumption [7,8]. Therefore, the efforts to save electrical energy will be paramount to all the buildings.

Generally, each building consists of multiple electrical loads that are used consistently or regularly. In commercial buildings and industrial buildings, lighting, motors, air-conditioning system or Air Handling Unit (AHU) system are the common loads used. However, other devices or Miscellaneous Electrical Loads (MELs) such as computers, printers, televisions, fax machines, oscilloscopes, furnaces and others also contribute to the energy consumption. Nevertheless, in general, air-conditioning consumes the most electrical energy consumption of the buildings [9]. In estimate, air conditioning systems use around 45% of electrical energy of the whole commercial buildings and dwelling areas [10].

Besides the use of electrical appliances and devices in buildings, the geographical and location of a building also influence the electric energy consumption, and indirectly affects the forecasting analysis. Geographical differences of the building will make a difference in the use of electrical equipment. This differentiation is related to several factors associated to the particular country, such as the weather condition, surrounding temperature where the country is located, as well as the seasons. According to Mirasgedis et al., the electrical energy consumption generally increases about 2.6% during summer due to the rise of daily temperature [11]. The use of air conditioning indeed consumes the most of electrical energy to provide comfort to the working space of the building. Cooling space will use a lot of energy if the building environment is quite hot. In contrast to temperate regions, the cooling space takes more time and uses less electricity. For example, in Saudi Arabia, which has a hot-humid climate, buildings consume more than 70% of total electrical energy usage, and during summer, the electrical energy demand gets higher [12]. Buildings in this region rely on the HVAC system to achieve the comfort space temperature [13]. In Australia, a sub-tropical climate country, about 70% of energy consumption is consumed by the HVAC system and has a very high demand for air-conditioning [14,15]. Marie and Julien, in their study, found that temperature is one of the major factors that determine the electricity consumption in Europe [16]. Meanwhile, the electricity load in Spain is influenced by the temperature, which is heating degree days [17]. Although the influence of temperature is the most [18–21], other factors also contribute to the electricity demand, such as humidity, wind speed, cloudiness, rainfalls and solar radiation [18].

In terms of time scale, generally, the hours of operation of a building varies, depending on the type of building. For example, the duration of electricity usage in industrial buildings is usually 24 h. However, there are industrial buildings that operate within working hours. For office buildings, the operation time is normally in working hours, usually starting from 8 am until 5 pm. For electricity consumption in the residential area, the electricity usage is maximum in the evening when all family members are at home. However, this electrical energy usage also depends on several occasions, such as holiday, festive and others. For a forecasting purpose, there are three categories of forecasting analysis, named as Short Term Load Forecasting (STLF), Medium Term Load Forecasting (MTLF), and Long Term Load Forecasting (LTLF). Each of these terms has different time ranges and different purposes of forecasting. The definition of time range is slightly different regarding to the research study. STLF usually takes time range that lasts for 24 h [22]. STLF time range is also defined as time range between 24 h, but up to only one week. For MTLF time range, the time range covers from one week, up to one year analysis. For utility companies, they will use the MTLF analysis to estimate the load demand in long term, which is useful for maintenance operation [23]. LTLF analysis involves a longer time frame than STLF and MTLF, and is usually conducted for future infrastructure plans [24]. For forecasting purposes, the precision in forecasting is the main issue in conducting the forecasting analysis; however there are difficulties due to the complexity of the system. Nowadays, there are many forecasting models developed by combining several methods, in order to solve the difficulties in forecasting and to find the best accuracy in forecasting.

There are several popular methods used for forecasting building energy consumption, which can be categorized into three, which are Engineering Method, Statistical Method and Artificial Intelligence Method. Among these methods, the most widely implemented method in forecasting is the Artificial Intelligence (AI) Method, which includes Artificial Neural Network (ANN) and Support Vector Machine (SVM) [25,26]. The other two methods of Engineering Methods and Statistical Methods are still applied, but some shortcomings have been identified in both these methods,

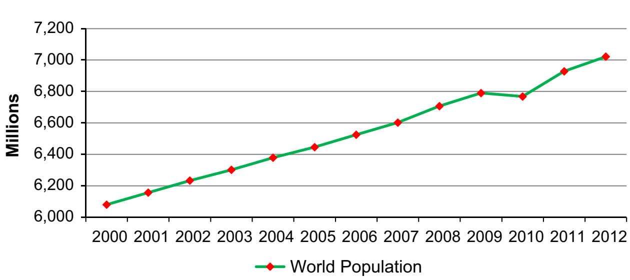

Fig. 1. World Population Pattern [3].

Table 1
Comparison between forecasting methods [25].

Methods	Model complexity	Easy to use	Running speed	Inputs needed	Accuracy
Elaborate engineering	Fairly high	No	Low	Detailed	Fairly high
Simplified engineering	High	Yes	High	Simple	High
Statistical	Fair	Yes	Fairly high	Historical data	Fair
ANNs	High	No	High	Historical data	High
SVMs	Fairly high	No	Low	Historical data	Fairly High

causing the Artificial Intelligence Method to have priority for application in forecasting analysis. Among the deficiencies identified in Engineering Method are its complexity which contributes to the difficulties to apply it practically and its lack of input information [25]. Meanwhile, the Statistical Methods has been found to have lack of accuracy and not flexible [25]. The application of Artificial Intelligence Method in building energy system had been discussed by Krarti and Dounis in 2003 and 2010 [27,28], which included forecasting, system modeling and control. For building energy consumption analysis, the ANNs are most widely implemented due to their best accuracy result and the ability of analyzing nonlinear problems. The ANNs also can learn from the historical pattern during analyzing the data. Besides that, it has capabilities in pattern recognition and pattern classification [29]. Some results from the Artificial Intelligence Methods and other methods from previous works are included for performance comparison in the next chapter. As referred from Table 1, as similarly reviewed by Zhao [25] in 2012, the accuracy of ANN and SVM seem to have better promising result for building energy forecasting, based on the historical data analysis. To evaluate the potential Artificial Intelligence capability, we had applied and tested the Artificial Neural Networks (ANNs) and Support Vector Machine (SVM) in buildings electrical energy consumption forecasting.

2. Artificial Neural Networks

ANNs are the most widely implemented methods in forecasting building energy consumption. However, there are some advantages and disadvantages needed to be acknowledged when ANNs are used, as listed in Table 2. Since the complexity of building energy system is very high due to several factors as mentioned previously, the ability of ANN in performing non-linear analysis is an advantage in executing buildings energy consumption forecasting. This section reviews the previous applications of ANNs in forecasting buildings energy consumption analysis.

The estimation of energy consumption of appliance, lighting and space cooling in the residential sector had been conducted by Aydinalp in 2002 using Neural Network [30]. In the study, the application of neural networks performance had shown its superiority in predicting when compared with an engineering model, owing to the lower correlation coefficient, R^2, and higher coefficient of variation, CV, value in the engineering model than the NN model, as shown in Fig. 2. In the following work in 2004, Aydinalp used neural network to model space heating and domestic hot water energy consumption [31]. The comparison between the NN model and engineering model showed that both had the capability in predicting. However, the higher value of CV and lower R^2 value indicated that the NN model has better performance, as shown in Table 3.

General Regression Neural Network (GRNN) was used by Ben-Nakhi in 2004 to predict the cooling load of public buildings [32]. In the analysis conducted, as the samples number increased, the GRNN started to show its fast learning and convergence to an optimal regression surface [32]. The accuracy of GRNN for use in predicting cooling load was significant due to its ability to predict the cooling loads, prior to the weather condition and it required less input than the building simulation software. The accuracy of the ANN guaranteed the GRNN approach to be reliable for use.

Gonzalez and Zamarreno [33], in 2005, used feedback neural network to predict the short term electricity load, which produced an excellent result for load forecasting in buildings. Furthermore, in their research, they suggested that there are three values that need to be studied, which are the number of neurons in hidden layers, the best size of data windows and the algorithm parameters. Nonetheless, in order to get satisfactory result, too many neurons is not necessarily needed, as explained by Eric [34] in 1996. Yang et al. [35] used adaptive artificial neural networks in

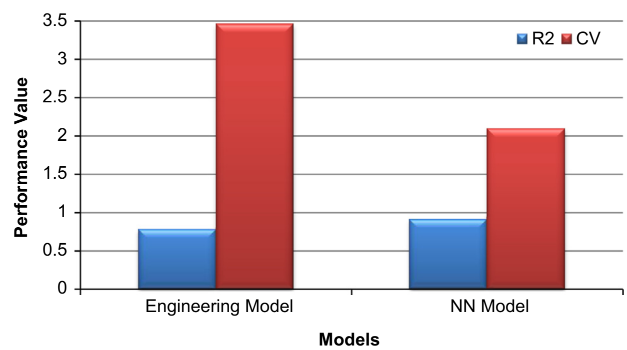

Fig. 2. Prediction performance between Engineering Model and NN Model [31].

Table 3
Prediction performance between Neural Networks and Engineering Models [31].

	Forecasting model	R^2	CV
Domestic hot water	Neural network model	0.871	3.337
	Engineering model	0.828	3.898
Space heating	Neural network model	0.908	1.871
	Engineering model	0.778	2.877

Table 4
Comparison between ANN and nonlinear regression models [37].

Year	Electricity consumption in intensive industry		
	Actual	ANN	Regression
2000	15342.46	15283.92	16792.82
2001	14856.34	14561.08	16188.65
2002	14370.23	14351.00	15583.68
2003	14574.89	14073.28	15094.45
	MAPE error	0.0099	0.075

Table 2
Advantages and disadvantages of ANN.

Artificial Neural Networks	
Advantages	Disadvantages
1. A Neural Network can execute the task that a linear program cannot 2. Neural networks are parallel in nature. When an element of the neural networks fails, it can continue without any problems 3. A Neural Network can learn and no need to be programed 4. Can be executed in any application 5. Can be implemented without any problem	1. The neural networks need training to operate 2. Needs to be emulated since the architecture of neural network is different from the architecture of microprocessor 3. For a large neural network, high processing time is required

building energy prediction. There were two adaptive ANN models used in this study, which were accumulative training and sliding window training. In real measurements, the prediction results were found to be more accurate when using sliding window technique. Karatasou et al. [36] discussed about the application of ANNs in predicting building energy consumption. In their study, the application of ANNs, together with statistical analysis, was found able to improve the applicability of ANNs in modeling and predicting building energy consumption.

The Artificial Neural Network (ANN) was used by Azadeh et al. [37] in 2008 to forecast long term electricity consumption in energy-intensive manufacturing industries. The comparison between the ANN and nonlinear regression model using error analysis showed that the ANN has good forecasting value for electricity usage, as shown in Table 4. The percentage of error analysis using Mean Absolute Percentage Error (MAPE) for ANN produced less error than the Regression. Alberto and Flavio [38], in the same year, conducted a comparison between simulation software and ANN for building energy consumption forecasting. They found that both models were effective in conducting building energy consumption forecasting. However, the ANN model was found able to offer superior prediction than the simulation software.

Back Propagation Neural Networks (BPNN) were applied by Yokoyama [39] in 2009 to predict cooling demand in a building. They proposed a global optimization method, called Modal Trimming Method, to identify model parameters [40]. Dombayci and Golcu [41] developed an ANN model to predict daily mean ambient temperature. The result showed that the developed model had the capability of predicting the temperature [42]. Each network for different number of neurons had been tested, in which the networks with six neurons produced the best result for this model. The fraction of variance, R^2, and RMSE for training were 0.9902 and 1.8524, while for testing, these values were 0.9888 and 1.9655, respectively [41]. Another prediction analysis was conducted by Xuemei et al. [43] to predict air-conditioning load using a hybrid of ARIMA and BPNN models. The case study result indicated that this hybrid model has the capability to reduce forecasting error, as shown in Table 5.

Wong et al. [44], in 2010, applied an artificial neural network for predicting office buildings energy consumption in subtropical climates. The performance of ANN in this analysis was measured by using Nash–Sutcliffe Efficiency Coefficient (NSEC). The value of 1 of NSEC indicated a perfect match of the predicted data. The NSEC result for ANN cooling model, heating model, electric lighting model and total building electricity used were found to be 0.994, 0.940, 0.993 and 0.996 respectively. These values indicated that the ANNs had very good predictive performance [44]. In the same year, Back Propagation Neural Network was used by Cheng-Wen [45] for predicting building energy consumption of heating and cooling loads in different climate zones. The analysis, conducted using BPNN method, could help engineers and architects in designing or planning for new buildings. With regard to the reliability and the accuracy in prediction at the early state, BPNN is significant for buildings design.

In the following year, the forecasting of building energy consumption, using ANN and hybrid Genetic Algorithm-Adaptive Network-based Fuzzy Inference System (GA-ANFIS), had been studied by Li et al. [46]. The comparative works between these two methods used two data sets of energy consumption from the Great Building Energy Predictor Shootout (S1) and from library building in Zhejiang University, China (S2) [46]. The result of forecasting was evaluated using coefficient of variation (CV), which indicated that the GA-ANFIS produced better performance of forecasting accuracy than ANN, as shown in Table 6. This was because the GA-ANFIS model produced smaller CVs when compared with ANN.

Another technique commonly applied for forecasting is the Group Method of Data Handling (GMDH). It is a relatively unexplored neural network model [47] that was introduced by Ivakhnenko in 1970, as a multivariate analysis method for complex systems [48]. The GMDH algorithm has the advantage of being able to avoid the difficulty of creating a mathematical model for the analysis being conducted [49]. In comparison to the other multi-layered neural networks, the GMDH architecture was not ready beforehand, but has been fully adjusted both structurally and parametrically during training [49]. GMDH has been successfully implemented to solve many prediction problems, such as in a research by Vicino et al. [50], which used GMDH for forecasting analysis, together with statistical techniques to predict energy demand [47]. Besides that, Elattar and Goulermas [51] also applied GMDH for short term load forecasting.

The application of GMDH by Srinivasan [47] in 2008, which was initially intended to predict energy demand, had shown the capability of GMDH in forecasting analysis. The comparison analysis, covering GMDH and five different forecasting models using MAPE, showed that GMDH had significantly produced more accurate result than the other models, in which the GMDH error analysis showed the lowest percentage, as shown in Table 7.

Table 5
Performance of different prediction models [43].

Forecasting model	Evaluation indices		
	RME (%)	MARE (%)	RMSE (%)
ARIMA	0.91	4.18	11.37
BPNN	0.88	3.82	10.76
ARIMA–BPNN	0.46	2.26	5.62

Table 6
Comparison between GA-ANFIS and ANN [46].

CV	ANN (S1)	GA-ANFIS (S1)	ANN (S2)	GA-ANFIS (S2)
Train	0.0893	0.100	0.0241	0.0229
Test	0.1030	0.0961	0.0323	0.0260

Table 7
Comparison result for different forecasting methods [47].

Sector	Forecasting method					
	Double moving average (%)	Single exponential smoothing (%)	Double exponential smoothing (%)	ARMA (%)	BPNN (%)	GMDH (%)
Residential	6.00	5.41	4.96	3.74	2.54	1.74
Commercial	2.58	2.46	3.07	3.11	2.56	2.04
Entertainment	5.16	4.80	4.70	3.90	3.86	2.69
Public lighting	1.82	1.59	1.61	1.86	1.34	0.83
Industrial	6.14	5.66	4.68	3.51	3.02	2.65
Non-industrial	6.06	6.20	5.30	3.7	3.2	2.64

Table 8
Analysis result of GMDH and ARIMA [52].

Model	**Stage**	**MAPE (%)**
GMDH	Training	4.42
	Forecasting	5.82
ARIMA	Forecasting	23.75

Xu et al. [52] applied GMDH in forecasting electric load demand. In this forecasting analysis, the GMDH model was compared with the ARIMA model using Mean Absolute Percentage Error (MAPE). The comparative analysis indicated that the GMDH was better at the forecasting stage due to the lower percentage of MAPE, as shown in Table 8. The proposed GMDH has two advantages, in which the GMDH is essentially automatic and the proposed methodology creates commendable improvements. Other than the single method, consolidation method can also be implemented in the forecasting analysis.

This section discusses some of the ANN methods that have been used, particularly in the analysis of energy consumption forecast in buildings. For the analysis involving non-linear problems, the use of ANN is one of the ways that are applicable for the accuracy of predictive analysis [53]. The ANN methods have been widely used in many applications and analysis in the engineering and non-engineering fields [54]. For the applications in the analysis of buildings electricity energy consumption forecasting, they are very prominent and capable of producing reliable results in forecasting accuracy.

3. Support Vector Machine (SVM)

Support Vector Machine (SVM) is one of the ten algorithms in data mining and also considered as one of the most robust and accurate methods among the well-known data mining algorithms [55]. SVM is also categorized as a new neural network algorithm for forecasting [56]. It is increasingly used in research and industry due to its highly effective model in solving non-linear problems [25]. Besides that, since it can be used to solve nonlinear regression estimation problems, SVM can be used to forecast time series. SVM was introduced by Vapnik in 1995, based on the Statistic Learning Theory (SLT) and Structural Risk Minimization (SRM) [57]. SVM so far has been widely used in various analyses such as regression, classification and non-linear function approximation. Thanks to the advantages of SVM algorithm in solving non-linear problems, it can be used to forecast energy consumption with high accuracy.

SVM was applied by Dong et al. [56] in 2005 to predict monthly buildings electricity consumption in tropical regions. The analyses on three years data of electricity consumption showed that SVM has a good performance in prediction. Li et al. [58], in 2009, used SVM to predict cooling load in office buildings. The results showed that the SVM had superior accuracy than the conventional back-propagation neural network. Besides the office buildings, Li et al. [59], in 2010, applied four different modeling methods, which were back propagation neural network, radial basis function neural network, general regression neural network and SVM, to predict the annual energy consumption for residential buildings. The training sample showed that the SVM and GRNN could be feasible and effective to apply in the prediction analysis. However, the test conducted to all methods indicated that SVM could predict with higher accuracy and better than the others, as shown in Table 9.

Table 9
Prediction error analysis for different models [59].

Model	Training sample		Testing sample	
	RMSE	MRE	RMSE	MRE
SVM	0.008	0.006	2.395	1.895
BPNN	0.010	0.008	14.462	13.149
RBFNN	0.009	0.007	12.440	10.825
GRNN	0.008	0.006	5.237	4.912

Table 10
Comparison result between ARIMA and SVM [60].

Model	Absolute error (%)		Relative error (%)	
	Max value	Mean value	Max value	Mean value
ARIMA	86.9	24.6	21.4	5.6
SVM	72.8	18.5	14.7	4.08

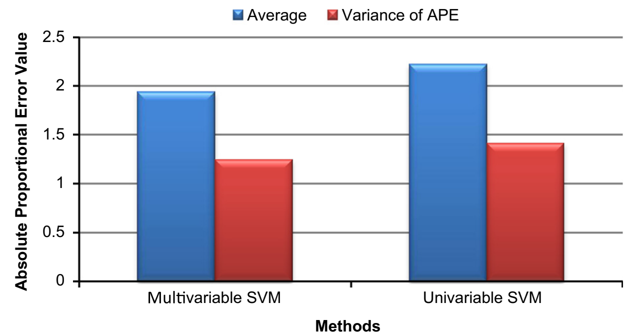

Fig. 3. Comparison between two methods using Absolute Proportional Error (APE) [61].

Table 11
Method comparison between BPNN and LSSVM [57].

Methods	Error analysis		
	RME	MARE	RMSE
BPNN	0.79	4.18	11.84
LSSVM	0.45	1.65	5.56

Hou and Lian [60], in 2009, applied SVM to predict cooling load for HVAC system. In this analysis, the ARIMA model was compared with SVM, and the error analysis showed that SVM had better performance than ARIMA, as shown in Table 10. Xing-Ping and Rui [61], in 2007, forecasted the electrical energy consumption in China using Support Vector Machine, which was categorized into two, which were multi-variable SVM and univariable SVM. The comparison analysis, using Absolute Proportional Error (APE), indicated that multivariable SVM had better forecasting result since the analysis result for multivariable SVM was lower than univariable SVM, as summarized in Fig. 3. The multivariable SVM showed a better forecasting result due to important factors which influence the electrical energy consumption which were considered in the multivariable SVM analysis. Lai [62] applied the Vapnik's learning theory to forecast energy consumption in residential buildings. The SVM-based algorithmic tools used in the experiments and analysis of the electrical consumption showed satisfactory results and were then utilized to make predictive modeling.

Jain and Satish [63], in 2009, used SVM in clustering based Short Term Load Forecasting. The implementation of SVM in this analysis was intended to forecast the next day load in energy utilities. Other than that, the proposed method did not require any heavy computational burden. For the same type of forecasting, Mohandes [64] showed that the SVM result for forecasting was better compared to the Auto Regressive modeling. The RMSE for testing data for SVM was 0.0215, while the value was 0.0376 for AR. The lower RMSE in the analysis indicated that the forecasting was more accurate. In another study, Bo-Juen et al. [65], in 2004, used SVM for load forecasting in the EUNITE competition. The proposed model to forecast the mid-term load forecasting was

successfully applied. However, another result came out from the experiment, indicating that the temperature or climate information might not be useful for mid-term forecasting.

Despite the many pros of SVM in conducting forecasting analysis, it has one major drawback, in which it has higher computational burden for the constrained optimization programming [66], and the higher computational burden will take time [67]. Hence, another technique has been derived and developed from SVM, known as Least Square Support Vector Machine (LSSVM). LSSVM is used to convert the inequality constraint of the original SVM into equality ones [67,68]. Xuemei et al. [57], in 2009, applied LSSVM to improve time efficiency of the prediction of building cooling load forecasting. The model comparison between the LSSVM and BPNN showed that the LSSVM achieved better prediction accuracy, as shown in Table 11. Since the LSSVM is quick and has correct learning performance when the training set is limited, it makes LSSVM as a new avenue in load forecasting. LSSVM model was also applied in Short Term Load Forecasting by Junfang and Dongxiao [69] in 2009. It was used to describe the nonlinear relationship between the load and influencing factors. The experimental result showed that LSSVM method is an effective method for load forecasting.

4. Hybrid model

Hybrid models for energy consumption forecasting are commonly used to get better accuracy of forecasting result from the existing developed model. In the energy consumption field, the accuracy of forecasting model is important because it is the basic analysis in making development plan and decision-making. In 2006, Fan and Chen [70] developed an adaptive hybrid method based on the Self Organized Map (SOM) and Support Vector Machine (SVM) to forecast short term load. The forecasting models were tested using the historical energy load from the New York Independent System Operator (ISO). Two sets of data were analyzed, which included the data for two test months and the data for regular workdays. The performance analyses of forecasting models, using Mean Absolute Error (MAE) analysis and Mean Absolute Percentage Error (MAPE), indicated that the hybrid model had the least error compared to the single model applied, as shown in Table 12.

Table 12
Performances analysis for different forecasting methods [70].

	Month				Work days			
	Winter		Summer		Winter		Summer	
	MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE
ISO	163.05	2.86	245.47	3.55	147.97	2.49	239.37	3.44
Single SVM	143.21	2.38	207.74	3.03	152.64	2.41	185.49	2.54
Hybrid network	106.97	1.82	162.20	2.29	91.83	1.49	155.17	2.11

Table 13
Forecasting model performances analysis using error analysis [71].

	ARIMA	ANN	Hybrid ARIMA–ANN
RMSE	895.57	925.66	62.45
MAE	820.7	−16410.1	73.8
MAPE	3.563%	−3.980%	0.311%

Wang [71], in 2012, utilized a hybrid of Artificial Neural Network and ARIMA model for energy consumption forecasting. The models were analyzed by using Root Mean Square Error (RMSE) analysis, Mean Absolute Error (MAE) analysis and Mean Absolute Percentage Error (MAPE) analysis. The analysis indicated that the hybrid model produced lesser error compared to the other models, as shown in Table 13. The small error resulting from the hybrid model showed that it has a good accuracy in forecasting analysis. The analysis on building energy consumption forecasting using hybrid models seems to produce a good accuracy result on forecasting. Hence, the ability of hybrid model in producing accurate result is reliable.

Besides the energy consumption fields, forecasting analysis has been applied in other fields, which require future projection based on current situation. In this section, the applications of GMDH and LSSVM in forecasting analysis are highlighted. Since the GMDH produces better accuracy in forecasting model and LSSVM has time efficiency as improvement for forecasting, the hybrid model of these methods should have the capability of improving forecasting accuracy.

Besides the use of the single model application of GMDH and LSSVM for forecasting, the combination of two techniques or hybrid has also attracted the attention of many researchers. The purpose of hybridizing the techniques is to produce better results of forecasting analysis, which is the forecasting accuracy. The GLSSVM was proposed by Samsudin [72] in 2010, to forecast tourism demand since the tourism expenditure has become an important source of nations. In the study, the GLSSVM was validated by using tourist arrival data, collected from the Johor Tourism Action Council Johor, Malaysia, which covered from January 1999 to December 2008. The tested GLSSVM showed better accuracy than the individual GMDH and LSSVM. Hence, GLSSVM indeed has the capability to forecast the nonlinear time series data.

In the following year of 2011, Samsudin [48] applied the GLSSVM to forecast the river flow in Selangor and Bernam. The river flow forecasting is an important component of hydrological process. Accurate forecasting results is useful in several hydrological sectors such as agriculture, hydropower station, and to ensure that the environmental flow is maintained. In the conducted analysis of forecasting model using river flow time series data, it was shown that the hybrid model produced better accuracy when compared with other individual models such as ARIMA, ANN, GMDH and LSSVM, as shown in Table 14. Owing to the ability of hybrid GMDH and LSSVM in non-linear time series forecasting, the implementation of GLSSVM into the building energy consumption forecasting is therefore potential, with regard to the application of individual methods, which are GMDH, SVM and LSSVM.

The GMDH model was also proposed by Samsudin [73] in 2008 to forecast the rice yields time series. At that time, the application of

Table 14
Prediction comparison between different methods [48].

1 Model	Selangor river				Bernam river			
	Training		Testing		Training		Testing	
	RMSE	*R*	RMSE	*R*	RMSE	*R*	RMSE	*R*
ARIMA	0.0914	0.7055	0.1226	0.5487	0.1049	0.7098	0.1042	0.5842
ANN	0.1065	0.5727	0.1092	0.6219	0.0602	0.9149	0.0709	0.8656
GMDH	0.1101	0.6733	0.1034	0.5850	0.0578	0.9216	0.0853	0.8387
LSSVM	0.0961	0.6747	0.1126	0.6269	0.0579	0.9319	0.0621	0.8727
GLSSVM	0.0853	0.7544	0.1123	0.6398	0.0290	0.9808	0.0642	0.8761

Table 15
Forecasting results using four different methods [74].

	Data series	RMSE			
		ARIMA	ANN	GMDH	KONDO
Testing	A	0.0631	0.0718	0.0692	0.0699
	B	0.0176	0.0152	0.0156	0.0162
	C	0.0118	0.0144	0.0115	0.0110
	D	0.0282	0.0277	0.0266	0.0247
	E	0.0999	0.0842	0.0785	0.0581
	F	0.0187	0.0321	0.0237	0.0250
Forecasting	A	0.0834	0.0896	0.0806	0.0754
	B	0.0248	0.0204	0.0200	0.0175
	C	0.0787	0.1320	0.0117	0.0109
	D	0.1578	0.0368	0.0351	0.0318
	E	0.1393	0.0729	0.0727	0.0765
	F	0.7946	0.1001	0.0638	0.0257

GMDH to forecast time series was still novel. The analysis was conducted on the same sets of rice yields data, using GMDH and ANN, in which the result showed that GMDH is an effective method for rice yields forecasting, while the ANN is good for time series modeling. Additionally, the combination of both methods can be applied to produce better accuracy of time series forecasting. In their following work, Samsudin and Saad [74] enhanced the conventional GMDH method to forecast rice yield data, obtained from Muda Agricultural Development Authority (MADA), Kedah, Malaysia. The study was conducted by comparing an enhanced GMDH method, known as KONDO model, with conventional GMDH, neural network and ARIMA. The results showed that the KONDO model was more competent in modeling and forecasting than the other models, as shown in Table 15. Another analysis which used the combination of GMDH and Genetic Algorithm (GA), had been conducted to improve forecasting accuracy. Samsudin et al. [75] used the yearly cancer death rate in Pennsylvania to measure the effectiveness of the combined method of GAGMDH. The analysis showed that the GAGMDH can improve the forecasting capability.

The success of GMDH in conducting analysis, along with its good accuracy, has been an attraction, since its application in forecasting analysis provides promising results for forecasting building energy consumption. Since the GMDH is relatively new in this forecasting application, there are many rooms to explore about this method, especially in forecasting analysis. Besides that, the use of LSSVM in forecasting analysis also cannot be neglected, since it has good accuracy forecasting result, based on previous researches. Moreover, in other fields, the combination of GMDH and LSSVM to improve the time series forecasting accuracy has shown its capability and potential. Since the GMDH and LSSVM have the ability to conduct non-linear problems, using hybrid GLSSVM could give better accuracy results for forecasting building energy consumption. Moreover, the GLSSVM model has not been applied to forecast building energy consumption currently. Hence, there are possibilities to use GLSSVM for forecasting building electrical energy consumption with good accuracy. Further researches need to be conducted to discover the possibility of GLSSVM in forecasting building electrical energy consumption.

5. Conclusions

This paper reviews the building energy consumption forecasting using Artificial Intelligent method. This method is currently used in the field of buildings energy forecasting and has received much attention from many researchers, with regard to its advantage to cope with the complexity of buildings system that is influenced by many buildings parameters. Among the AI methods, the Neural Network and Support Vector Machine are the widely used models. The researches conducted using these models mostly aimed to find better forecasting performances, in terms of the forecasting accuracy. Since the applied models have their own advantages and disadvantages, it is hard to decide which one is the best in forecasting. Combining the models can ensure better forecasting performance. The proposed hybrid model of GMDH and LSSVM of GLSSVM in this review has a bright potential in forecasting, with regard to the successful application of these two methods in other time series-forecasting fields. The potential of forecasting using GLSSVM will be evaluated by conducting the analysis of GLSSVM to the building electrical energy consumption. The precision of forecasting analysis is given priority in this study, in which the forecasting results were evaluated by using the error analysis such as RMSE and the correlation coefficient. In this study, the proposed hybrid method was compared with other single methods such as GMDH, LSSVM and ANN for validating the hybrid method performance.

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